Analysis and Simulation of System Identification Based on LMS Adaptive Filtering Algorithm

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Abstract

This paper presents Adaptive Filtering and the least mean square algorithm which is widely used in Adaptive system. It realized the model and simulation of system identification Based on LMS algorithm by matlab and simulation. It can be seen that the adaptive FIR filter can simulation the unknown system well. Thus it can be got the system function of the unknown system through the parameters of the adaptive FIR filter and It can be carried out the function of the same hardware reconfiguration of the unknown system.

Keywords

Adaptive Filtering; Least Mean Square Algorithm; System Identification

Introduction

Adaptive signal processing is an important branch of signal and information processing and part, it has been a hot research topic in the field of signal processing. It has been widely used in digital communication, radar, sonar, seismology, navigation system, biological medicine and the industry control field after 30 years of development.

Adaptive filter, It is the use of filter parameters at the previous results obtained, to adjust the filter parameters and frequency response of the present moment automatically through feedback, in order to adapt to the statistical characteristics of the signal or noise varying with time., so as to achieve the optimal filtering.

In this paper, we realize the unknown system identification based on LMS adaptive algorithm, and the simulation results prove the new algorithm has we can get better result through the MATLAB simulation.

Adaptive Filter and LMS Algorithm

The adaptive filter is a kind of special Wiener filter and it can adjust the parameters automatically. when designed it need not to know the statistical characteristics of the input signal and noise in advance, it can gradually "understanding" in the work process or to estimate the desired statistical properties, and then automatically adjust its parameters, in order to achieve the best filtering effect.

There are two input: X (n) and D (n), two output: Y (n) and E (n), both are time series in the Fig1. The X (n) can be not only a single input signal but also multiple input signals. These signals represented different content In different application background.

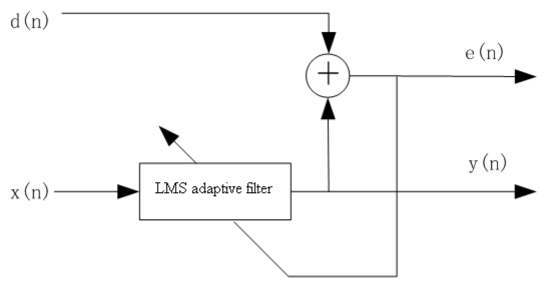

FIG 1 THE SCHEMATIC DIAGRAM OF ADAPTIVE FILTER

The input vector is

$$X(n) = [x(n)\ x(n-1) \cdots x(n-M+1)]^T \qquad (1)$$

As shown in Figure 2

The weighted vector (i.e. filter parameter vector) is

$$W(n) = [w_1(n)\ w_2(n) \cdots w_M(n)]^T \qquad (2)$$

The output of the filter is

$$y(n) = \sum_{i=1}^{M} w_i(n) x(n-i+1) = W^T(n) \qquad (3)$$

$$X(n) = X^T(n)W(n)$$

Y (n) with respect to filter the desired output d (n) error is

$$e(n) = d(n) - y(n) = d(n) - W^T(n)X(n) \tag{4}$$

According to the minimum mean square error criterion, the optimal filter parameters should keep the mean square error is the least, in W (n) is a constant vector case, the mean square error expression of n is at the moment

$$\xi(n) = E[e^2(n)] = E[d^2(n)] - 2P^T W(n) + W^T(n) R_x W(n) \tag{5}$$

Among them, $E[d^2(n)]$ is the variance of expected response D (n), $P = E[d(n)X(n)]$ is the cross-correlation vector of input vector and the expected response D (n), $R_x = E[X(n)X^T(n)]$ is the autocorrelation matrix of input vector X (n). On W (n) derivative, and take the derivative equal to zero, then the canonical equation will be obtained.

$$\frac{\partial \xi}{\partial W} = -2P + 2R_x W_{opt} = 0 \tag{6}$$

When R_x is the full rank, the canonical equation has a unique solution

$$W_{opt} = R_x^{-1} P \tag{7}$$

This solution is called Wiener solution. When $W = W_{opt}$ the minimum of mean square error function (i.e., the minimum mean square error) is equal to

$$\xi_{\min} = E[e^2(n)]_{\min} = E[d^2(n)] - P^T W_{opt} \tag{8}$$

The computational method for inverse of R_x will be get the big, Gradient method is often used in practice.

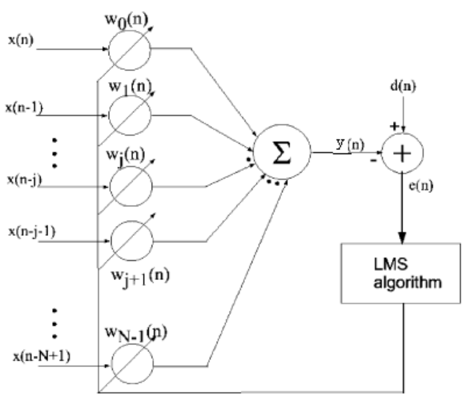

FIG 2 ADAPTIVE LINEAR COMBINER

System Identification Based on LMS Algorithm

System Identification

The unknown system identification is shown as the fig 3. It is found that the adaptive filter and another unknown transfer function of the filter were inputted at the same time x(n). The output d(n) of unknown controlled object is the output of the all system.

In the convergence, the output of adaptive filter $\hat{d}(n)$ is in an optimal manner similar to the d(n). It is matched that the order of adaptive filter which provided and unknown controlled object, and the input signal x (n) is the generalized steady-state, coefficient of the adaptive filter will be convergent to the same value of unknown, controlled object.

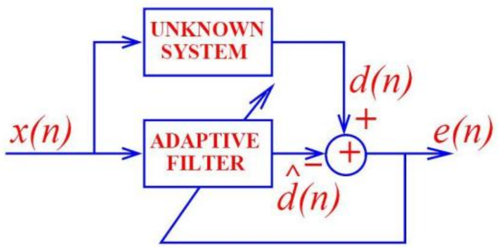

FIG 3 SYSTEM IDENTIFICATION PRINCIPLE DIAGRAM

System Identification Modeling and Matlab Simuliation

The actuating signal x (n) is usually random sequence in Figure 3 because of its wide bandwidth and traversing the entire band, it can encourage all modal system and obtain system parameters more accurate.

By using the LMS algorithm to adjust the tap coefficients of adaptive filter in this paper, the unknown FIR filter object is set to 16 order, the corresponding order of adaptive filter is 16 too, the initial tap coefficients is 0, step size parameter μ of LMS algorithm is set to 0.0001. The excitation signal is the white noise sequence for the mean value is 0 and the variance is 100.

The simulation result is as shown in Figure 4 and figure 5. The black line is the output of x (n) which is through the unknown plant the red line is the output of the adaptive filter in Figure 4 .It can be seen, after a period of time updating, the red line and black line almost entirely coincidence, the error tends to be 0. It is the tap coefficients of adaptive filter steady state and the tap coefficient of the actual system by comparison, we can see the coefficients of the adaptive filter and the parameters of unknown object is basic consistent. In Figure 5.

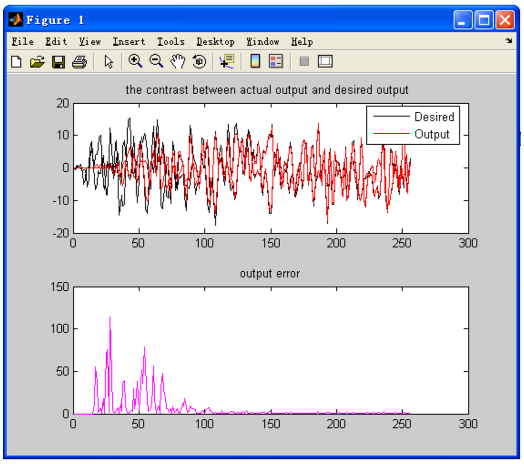

FIG4 OUTPUT AND ERROR OF THE SYSTEM

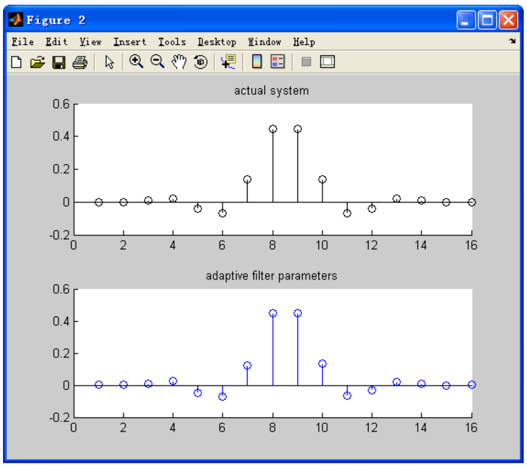

FIG5 THE RESULT SYSTEM IDENTIFICATION

Through the adaptive FIR filter, modify the system function constantly, make the full approximation with parameters of unknown system, reduce the error, and achieve the purpose of system identification. In view of unknown system of Butterworh type, using LMS algorithm, simulation results using Matlab as shown in figure 6.

It can be seen from the Figure 6 that the adaptive FIR filter can simulation the unknown system well, and Close to processing effects of the original signal .Thus It can be got the system function of the unknown system through the parameters of the adaptive FIR filter and It can be carried out the function of the same hardware reconfiguration of the unknown system.

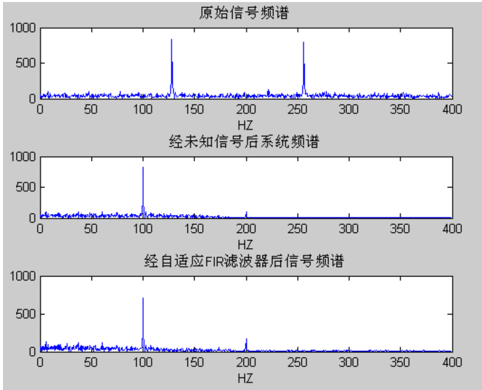

FIG. 6 THE SPECTRUM OF SIGNAL PROCESSING SYSTEM

Simulink Simulation of System Identification

Simulink is a visual simulation tool of MATLAB, it is a software package to realize the modeling, simulation and analysis of the dynamic system .It is widely used for modeling and simulation of linear systems, nonlinear systems, digital control and digital signal processing. This paper uses the DSP provided by Simulink tool package to realize channel identification function. It is a block diagram of the connecting channel identification system in Fig 5. The FIR filter (Discrete FIR Filter) is set to 8 order, the tap coefficients is for [1 2 3 4 5 6 7 8], the parameter is set for 8 order and μ=0.0001 in LMS module. Then running, and observing by the oscilloscope at the output, at last the change situation will be get for tap weights of adaptive module

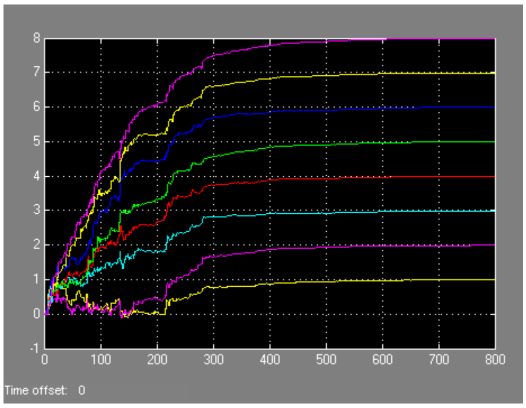

FIG7 THE TAP WEIGHTS OF THE ADAPTIVE MODULE

Each curve corresponds to a tap coefficient of the adaptive filter in Figure 7, there is a total of 8, and the initial value is 0. It can be seen after a period of adaptation, the value convergence to tap coefficients of practical FIR filter of [1 234567 8], and achieve system identification function well.

Conclusion

This paper analyzes the LMS adaptive filter algorithm and simulates the unknown system using LMS algorithm by MATLAB software. At the same time, visual simulation tool Simulink is used for simulate also. The system finally realizes the identification function.

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